When do we attain our objectives? On the role of indicators, values and uncertainty in environmental management

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ACADEMIC DISSERTATION

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LIST OF ARTICLES INCLUDED

This thesis consists of a summary part and the following articles.

I Laurila-Pant, M., Lehikoinen, A., Uusitalo, L., & Venesjärvi, R. (2015). How to value biodiversity in environmental management?. Ecological indicators, 55, 1-11.

II Laurila-Pant, M., Mäntyniemi, S, Östman, Ö., Olsson, J., Uusitalo, L. & Lehikoinen, A. A Bayesian approach for assessing the boundary between desirable and undesirable environmental status – an example from a coastal fish indicator in the Baltic Sea. Manuscript.

III Laurila-Pant, M., Mäntyniemi, S., Venesjärvi, R., & Lehikoinen, A. (2019). Incorporating stakeholders' values into environmental decision support: A Bayesian Belief Network approach. Science of The Total Environment, 697, 134026.

The articles are referred to in the text by their roman numerals (I-III).

Authors' contribution to the articles:

I M. Laurila-Pant had the main responsibility in formulating the structure of the article and carrying out the literature review. The original idea of the work came from A. Lehikoinen and L. Uusitalo, who also were the supervisors of the work. M. Laurila-Pant was the corresponding author of the article. R. Venesjärvi provided ideas and comments on the article. All the authors participated in writing the article.

II M. Laurila-Pant was responsible for the original idea together with A. Lehikoinen and L. Uusitalo. M. Laurila-Pant together with S. Mäntyniemi were responsible for the practical development of the method, as well as the data handling and coding work. Ö. Östman and J. Olsson provided methodological ideas and comments. All the authors participated in writing the manuscript.

III M. Laurila-Pant was responsible for the original idea together with A. Lehikoinen and R. Venesjärvi. M. Laurila-Pant had the main responsibility in designing and implementing the stakeholder interviews and processing and analysing the data. M. Laurila-Pant and S. Mäntyniemi were responsible for the practical development of constructing the Bayesian models. M. Laurila-Pant interpreted the results together with A. Lehikoinen. All the authors participated in writing the article.

CONTENTS

ABSTRACT

In environmental policy and management, the main objectives are to protect and enhance the environmental status so that we can preserve the services and benefits ecosystems provide for the society. To evaluate whether the management objectives are met, there is a need to measure the prevailing status of the system in focus, and to define the desirable versus the undesirable state. How these tasks are implemented will impact our judgement about whether the system needs restoration or not, or if ongoing or planned exploitation of natural resources can be seen as sustainable. Indicators thus provide means for the precise definition of the objectives by setting measurable target states to be achieved.

However, it is not straightforward to judge, whether or not the objectives have been attained. The first question is, what we should measure, i.e. *what is an appropriate indicator*. The second question is, what the sufficiently good status of the indicator is, i.e. *how to define the target level*. Third, after we have decided what to measure and how to interpret the measurements, we have to think, *how the different decision criteria are weighted* in relation to each other. This thesis approaches the above-mentioned questions from the multidisciplinary and probabilistic perspective, providing novel ideas and tools.

Maintaining biodiversity is one of the key objectives mentioned in the Marine Strategy Framework Directive (MSFD) and the Baltic Sea Action Plan (BSAP). Article I of the thesis reviews alternative metrics for measuring (i.e. indicating) biodiversity and discusses the ecological, economic and sociocultural perspectives to its valuation. The paper suggests integrating these three perspectives into a multi-objective framework. Furthermore, a formal guideline for decision support is proposed when quantitatively evaluating alternative management decisions against biodiversity.

Article II elaborates the uncertainty related to the process of determining the prevailing status of an indicator as well as the boundary value used as the threshold between a desirable (Good Environmental Status “GES”) and a non-desirable state (“Sub-GES”). The current indicator-based management

protocols such as the MSFD and the BSAP have not acknowledged the uncertainty of the GES boundary value, instead, the boundary value is given as a fixed value with no associated uncertainty. Article II presents an alternative way to define the target level and assess the prevailing status of one ecological indicator, the abundance of perch (*Perca fluviatilis*) - an indicator adopted by both BSAP and MSFD to represent the status of coastal fish communities in the central and northern Baltic Sea. A Bayesian model is developed to evaluate the prevailing relative abundance and the GES boundary for it while acknowledging the uncertainty related to these estimates.

Multi-Criteria Decision Analysis (MCDA) is an approach used to frame and formally solve decision-making problems with multiple, often contradictory objectives. As society at large covers a variety of interests towards the services and benefits that ecosystems provide, the unavoidable trade-offs in environmental multi-objective decision-making processes easily lead to conflicts. In Article III, a Bayesian approach is developed to quantify the uncertainty about the stakeholder groups' consensus concerning the valuation of ecological attributes. When integrated into a MCDA model, it is possible to visualise what we know about the level of disagreement or agreement and analyse the optimal decisions from the perspective of each group.

The qualitative verbal management objectives (e.g. the "*sustainable development*" or "*good environmental status*") are vague in their precise meaning and can thus complexify the societal discourse. Indicators can be thought to specify their definitions. By setting quantitative metrics for expressing the objectives and defining the rules for their weighing, they allow transparent discussion and judgement whether the objectives are actually met or not. However, the use of indicators does not remove the uncertainty nor the value judgements related to environmental decisions. The inherent uncertainty that arises from the limited knowledge of the system - both the ecological and social part of it - cannot be avoided. However, by adopting a multi-disciplinary perspective which utilises modern modelling methods and normative decision theory, this thesis demonstrate a probabilistic view on the issue and develops tools to tackle it.

1 INTRODUCTION

The health of the Earth's ecosystems is an essential part of the life-support for the human species and all other forms of life. However, the growing human populations and the accelerating demand on natural resources poses the biggest threats on the health of ecosystems (Cohen, 1995; McKee et al., 2004; Steffen et al., 2015; Tilman et al., 2017) and ecological resilience (Allen et al., 2016). Ecosystems are under multiple simultaneous and interconnected pressures due to climate change, eutrophication, habitat loss, overexploitation, pollution and many others (Crain et al., 2009; Halpern et al., 2008; Korpinen et al., 2012; Grizzetti et al., 2017; Olsen et al., 2018), and are experiencing losses in biodiversity, ecosystem functioning and the production of ecosystem services. Ecosystem services provide food, transportation, and cultural and recreational services for the people (Costanza et al., 1999), thus the health of ecosystems is not only ecologically important but is also recognized as having economic and sociocultural significance.

In addition to this, today's environmental management problems are multidisciplinary and complex, where ecological information alone is insufficient. Environmental management is not only about managing the environment itself, but more importantly, it is about managing human behaviour and the behavioural drivers creating the pressures on ecosystems (Jager and Mosler, 2007; Vlek and Steg, 2007). Society values the consequences of the management decisions and thus defines the objectives by using its own preferences and sociocultural viewpoints. The viewpoints, however, vary according to what each actor has at stake (Scholte et al., 2016; Ruiz-Frau et al., 2018). As the viewpoints can be contrasting, the tension between the actors involved cannot always be avoided (Minteer and Miller 2011).

Complex socio-ecological problems, where the high degree of disagreement and uncertainty around the decision-making process makes it impossible to find one optimal solution, are termed as *wicked problems* (Rittel and Webber 1973; Balint et al., 2011). The environmental management decisions should be made across sectoral boundaries, interlinking the ecological and social values in the same decision analytic framework to improve the planning and management of the sustainable use of natural resources and allocation of those activities. The traditional sectoral –based and fragmented management have been found to be insufficient to capture this type of complexity (Bigagli, 2017; Smith et al., 2017).

This has created the need to develop a more comprehensive formal framework, labelled as Ecosystem-Based Management (EBM), which recognise the complexity and interactions within ecological systems, but also between the ecosystem and society (Ruckelshaus et al., 2008; Gregory et al., 2013; Langhans et al., 2019). The strong policy integration regarding objectives, knowledge exchange, methods, and tools, as well as engagement, is essential when aiming for long-term sustainable management in ecosystems (Langhans et al., 2019). The EBM is a collaborative framework aiming to capture more holistically, what needs to be protected when the ultimate goal is healthy and productive ecosystems. The EBM provides a formal basis for international treaties such as the Convention of Biological Diversity (CBD; UNEP, 1992), and in the indicator-based environment management schemes such as the Marine Strategy Framework Directive (MSFD; European Commission, 2008) and the Baltic Sea Action Plan (BSAP; HELCOM, 2007).

The EBM aims *to promote sustainable development and management, where the focus is in meeting the present needs without risking the ability of future generations to meet their needs* (Brundtland, 1987; Tallis et al., 2010; Berg et al., 2015; Soma et al., 2015). The sustainable environmental management, in turn, is composed of three pillars that are economic, environmental, and social (Barnard and Elliott, 2015). The three pillars can be either viewed to have equal importance in environmental management (Young, 1997; Newport et al., 2003; Morse, 2015), assuming that balance can be achieved (Young, 1997). Alternatively, Dawe and Ryan (2003) proposed that the three pillars of sustainability should be hierarchical, where the economy is seen as a subsystem of human society and social wellbeing, which is itself a subsystem of environmental sustainability (Fig. 1). The latter, so-called *strong sustainability model*, thus views the environmental sustainability as the ultimate limiting element, recognizing the healthy environment is a prerequisite for social wellbeing and that the monetary system is relevant only as part of the human society.

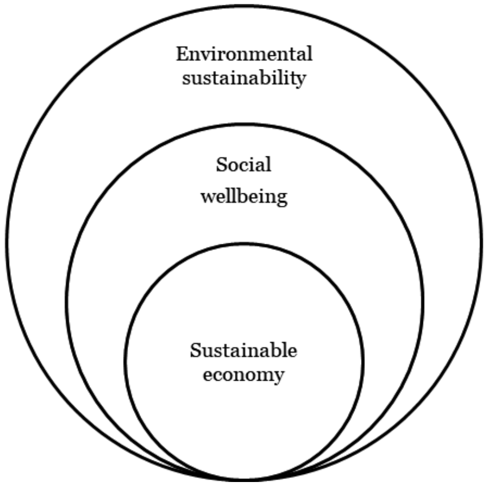

Figure 1. The hierarchical, *strong* model of sustainable development. The relationship between the three pillars of sustainability objectives suggest that both economy and social wellbeing are constrained by environmental limits.

Thus, if following the strong sustainability model, environmental policy and management should prioritize the ecological status to safeguard a liveable Globe and preserve the services and benefits ecosystems provide for the society (Borja et al., 2013, Borja et al., 2016). Environmental protection requires the ability to quantitatively measure the current status of the system in focus and describe the desirable and undesirable states of it. How these tasks are executed may have a major impact on our judgements concerning whether the exploitation of natural resources can be seen as sustainable or if protective actions are needed. However, the management objectives can be imprecise in their meaning, lacking quantitative description (Hugé et al., 2013; Boyes et al., 2016), and eventually leaving a lot of room for interpretation and thus complicate the mutual understanding between the parties involved.

The main aim of this thesis is to recognize and analyse the role of values and uncertainty associated with the target setting in environmental management. Through one review article and two research articles (appendices I-III), this thesis addresses the following research aims:

I. Defining appropriate indicators to judge whether the management objectives are attained.
II. Clarifying the sufficiently good status of an indicator by acknowledging and estimating uncertainty of the quantitative target level to be achieved.
III. Acknowledging the role of valuation, i.e. to determine how the different decision-criteria (i.e. attributes) can be weighted.

Article [I] takes a decision-analytic standpoint by discussing the ecological, economic and sociocultural metrics for valuing biodiversity in multidisciplinary environmental decision-making problems. The work analyses the interplay between these three perspectives and suggests integrating them into a multi-objective ecosystem-based management (EBM) framework. In the end, a sequence of steps to follow when quantitatively evaluating environmental management against biodiversity is proposed. Article [II] studies the uncertainty associated with the indicator-based status assessments, used to judge whether the management objectives are attained (i.e. whether the "*the Good Environmental Status*" is attained or not). The currently used indicator-based protocols (e.g. MSFD and BSAP) do not fully acknowledge and estimate the uncertainty rising from different sources. Therefore, this work aims to propose a Bayesian approach to define the quantitative target level, i.e. boundary value between a desirable (Good Environmental Status "GES") and a non-desirable state ("Sub-GES") and assess the prevailing status of one ecological indicator, the abundance of perch (*Perca fluviatilis*) - an indicator adopted by both BSAP and MSFD to represent the status of coastal fish communities in the central and northern Baltic Sea. Lastly, Article [III] focuses on the mutual weighting of multiple parallel management objectives (i.e. decision-making criteria) - in this case ecological attributes to be maintained as part of a marine spatial planning process. The article presents an approach for incorporating stakeholder groups' views into the environmental planning and decision-making process. The study presents a Bayesian approach to combine the variety of perceptions, quantifying the uncertainty about the stakeholder group consensus and demonstrates how the results can be integrated in a formal decision support model.

2 CONCEPTS AND METHODS

2.1 Decision-making and decision analysis

Environmental policy and management problems are inherently multifaceted and wicked (Rittel and Webber 1973; Balint et al., 2011), and thus involve inevitable compromises and uncertainties (Uusitalo et al., 2015) in different parts of the rational decision-making process. In this thesis, formal decision analysis is the key conceptual framework used to address decisions in a systematic way (Keeney, 1982). Formal decision analysis identifies, represents and formally evaluates all the aspects and consequences related to the decision-making process (Howard, 1988). For example, regulatory bodies (e.g. policy-makers, environmental permit authorities, environmental protection agencies) i) grant permissions for developers (e.g. wind farm operator, a dredging company, industrial plan) using ecosystems or ii) decide whether remediation actions are needed to improve the status of the system (Boyes and Elliott, 2014, 2015; Elliott, 2014). Formal decision analysis can assist in selecting when to grant permission for actions, which action to select, or where to allocate actions by integrating knowledge, and allows to acknowledge the uncertainty and visualize the results (Barton et al., 2012; Lehikoinen et al., 2014; Rahikainen et al., 2014). Therefore, it is a systematic quantitative approach allowing mutual rating between different management strategies. The key aim of formal decision analysis is to identify those actions or policies that simultaneously maximize the expected utility and minimize the expected risks and costs (Keeney, 1982; Burgman, 2005; Kiker et al., 2005).

To translate and communicate key features of complex environmental management problems to regulatory bodies, researchers and other stakeholders, a framework to conceptualize environmental management issues is needed. Figure 2 illustrates the DPSIR (Drivers–Pressures–State change–Impacts on society–Responses) framework for environmental problem structuring. DPSIR is utilized in various environmental management cases to represent key elements and their causal interactions in the socio-ecological systems; the actual or predicted human-induced impacts on the

Box 1. Concepts related to the decision-making as they are denoted in this summary.

Decision analysis: a normative practice of decision-making including procedures, philosophies, methods, and tools for identifying, clearly representing, and formally assessing important aspects of a decision. To define formally optimal courses of actions by applying maximum expected utility principle and to illustrate the outcome of the formal decision analysis for decision makers and other agents. (Keeney, 1982; Howard,1988)

Decision theory: a theory of rational decision-making. Divided into two disciplines: descriptive decision theory, which aims to analyses how people actually make decisions, and normative decision theory, which aims to analyse the outcomes of decisions or how people are required or ought to choose when faced with decision problem. (Peterson, 2009)

Decision-making: a process of identifying and selecting between alternative choices based on the values and views of a decision-maker. (Keeney, 1982; 1996)

Rational decision-making and planning model: a multi-step process for making rationally sound decisions: 1) definition of the problems and objectives, 2) identification of alternative actions or policies, 3) evaluation of alternative actions or policies, 4) implementation of decisions, and 5) monitoring of effects of actions. (Taylor, 1998)

Multi-criteria decison analysis: an approach to consider multiple potentially conflicting decision criteria in decision making. Helps a decision maker to structure the problems and acknowledge other stakeholders' values and judgement (Belton and Stewart, 2002)

environment and the interdependence of the components (Smeets and Weterings, 1999; Atkins et al., 2011; Patrício et al., 2016a; Elliott et al., 2017). The DPSIR framework assumes a chain of causal relations beginning with the *Drivers* that are forces to motivate human activities related to the basic human needs (e.g. food, air, drinking water, goods, and safety). These Drivers create *Pressures* on the environment through different anthropogenic activities (e.g. extraction of living resources, transportation, agriculture, and coastal infrastructure) that directly or indirectly affect the *State change* of the ecosystem (e.g. degrading habitats, reducing population size, changing population structures and increasing eutrophication). The changes in the ecosystems induce *Impacts on society*, meaning the human perspective on how the loss or gain of the ecosystem status is valued. – Based on the *Impacts on society* -element, the need for *Responses* is defined. These are management measures or actions to mitigate or restore the ecosystem status via the links between the *Drivers*, *Pressures* or *State change*.

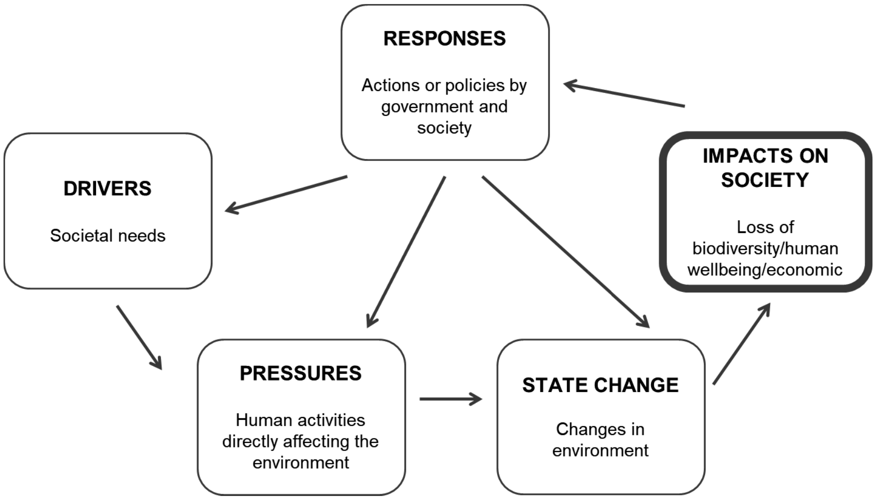

Figure 2. The DPSIR framework to structure problems in complex environmental management analysis. Representing the key theme in the focus of the thesis, the *Impacts on society*-element is highlighted.

The special focus of this thesis is to define the *Impacts on society* as this element includes the decision criteria linked to the attainment of management objectives (Fig. 2). When the observed (Article [II]) or predicted (Article [III]) changes in terms of decision criteria are quantified, this information can be used to indicate the need for management measures and to search for optimal management strategies. Indicators are technical tools used to quantitatively measure the changes in target attributes. In order to use indicators to define whether the objective is attained or not, the target level of the indicator needs to be set. Depending on the target level, the quantitative boundary value defines whether the measured prevailing status of the system is above or below the societally approved threshold level. However, as it is only possible to make an estimation of the actual status by using selected indicators, the status evaluations always includes uncertainty that should be acknowledged to avoid the chance of misclassification of the status (Article [II]).

However, perspectives in valuing the changes are manifold. Different ecological, economic or sociocultural viewpoints may rise when studying how the society perceives the loss or gain in the state of a particular attribute used as a decision criterion (Article [I]). Therefore, all variety of views should be taken into account when aiming for a collectively fair and rational decision-making process (Dietz, 2003). Also, when the attainment of the environmental objectives is evaluated by using multiple, even contradictory, decision criteria, it is challenging to avoid disagreement among the associated individuals and parties. By analysing the level and type of the disagreement within and between different stakeholder groups can help in identifying a collectively more optimal management strategy (Article [III]).

2.2 Bayesian inference and decision support

As this thesis focuses on the heterogeneity of views, stochastic variability in data and the following uncertainty in environmental management problems, the Bayesian approach is a natural methodological choice. There are many theoretical introductory books about Bayesian statistics that provide a basis for the approach (e.g. Gelman et al., 2013; Kruschke, 2014; Blasco, 2017). In Articles [II] and [III], the aim was to evaluate and acknowledge in the decision analysis the uncertainty about unknown population parameters; related to the target state between the desirable and undesirable environmental status [II] and the opinions of the stakeholders [III], respectively. These methods are widely used in the field of population analyses and fisheries stock assessments (e.g. Michielsens et al., 2006; Mäntyniemi et al., 2013; 2015) where the interest lies on those hidden population parameters that are not directly observable. However, in the environmental status assessment and participatory decision-making protocols these types of approaches to acknowledge and estimate uncertainty about these hidden population parameters is lacking.

In decision-making science, uncertainty is defined as a lack of exact knowledge (Refsgaard et al., 2007; Ascough et al., 2008). There is extensive literature on the categorization of different types of uncertainties (e.g. Walker et al., 2003; Burgman, 2005; Refsgaard et al., 2007). Uncertainty is often divided into three categories as epistemic, linguistic and aleatoric uncertainties. Epistemic (knowledge) uncertainty reflects imperfect knowledge, which could be reduced by further research and empirical studies. Epistemic uncertainty can include uncertainty in systematic and measurement errors, model uncertainty and subjective judgement. Linguistic uncertainty arises as our natural language is not exact and is distributed into vagueness, context dependence, ambiguity, indeterminacy and under specificity. Aleatoric uncertainty rises from the inherent randomness and natural variability of the system.

Bayesian inference applies the Bayes' theorem (Lunn et al., 2012; Gelman et al., 2013) to update the beliefs concerning a hypothesis as more information becomes available. The person implementing the analysis has to specify their choices and prior assumption, in other words, the probability is handled as a subjective degree of belief (Huber, 2005; Berger, 2006). These choices are related to a) the exact model structure (the dependencies between the parameters of interest, i.e. mean values and measures of variation), b) the type of the distribution of the values within the parameter of interest (e.g. normal, beta, etc.) and c) the prior knowledge (*i.e.* prior distributions describing the level of knowledge about the parameter of interests before seeing the data) (Kruschke, 2014).

In Bayesian inference, the initial knowledge (prior distribution) is updated when more information (data, interpreted via the likelihood function) becomes available, and thus creating the new updated knowledge about the topic of interest (posterior distribution) (Gelman et al., 2013). Bayesian inference computes the posterior probability according to Bayes' theorem, which can be written mathematically as

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \qquad (1)$$

, where θ refers to our parameters of interest, in other words, some event or hypothesis we want to learn about, and y is the observable data. Therefore, $p(\theta)$ and $p(\theta|y)$ are the prior (*"probability of the hypothesis before introducing the new data"*) and posterior (*"probability of the hypothesis, given the new data"*) parameter distributions, respectively, and the term $p(y|\theta)$ denotes the probability density of data y given the parameters θ. The term $p(y) = \int p(y|\theta)p(\theta)d\theta$ is the marginal (predictive) probability of y to evaluate how probable is the new data under all possible hypotheses. Thus, $p(y)$ acts as normalizing constant ensuring that $p(\theta|y)$ is a valid probability distribution integrating to 1.

Adding prior information is a unique feature of Bayesian statistical inference, which allowsthe use of available knowledge about the subject before collecting new data (Ellison, 2004; Van Dongen, 2006). Therefore, any knowledge about the subject beforehand should be given as prior distribution. Priors are given as probability distribution incorporating the related uncertainty of each parameter. These express how much is known about the subject before the evidence is disclosed. The level of prior knowledge can vary from fully informative (i.e. having exact knowledge of the subject) to uninformative (i.e. maximal uncertainty, where all the possible outcomes are equally likely) (Van Dongen, 2006). When the previous publications, expert knowledge or data of the subject are lacking and it is preferred to have a prior with minimal influence on our inference, an uninformative prior is typically selected. Then the aim is to maximize the role of the observed data in the estimated parameters compared to the priors (Van de Schoot et al., 2014). The interpretation of data is controlled by the prior knowledge about the link between parameters θ and data y, which is encoded in $p(y|\theta)$ (Equation 1).

The key difference between Bayesian and frequentist statistics is how the probability is utilized and introduced. Bayesian statistics gives probabilities for both hypotheses and data but both Bayesians and frequentists assume that the specified hypothesis (parameter specifying the conditional distribution of the data) is true and that the observed data is sampled from that conditional distribution (Ellison, 2004; Blasco, 2017). If the interest lies in the estimation of uncertainty about a parameter of interest, it can be achieved using the Bayesian approach. Conversely, the frequentist approaches, including bootstrapping, provide measures of uncertainty (e.g. standard error of the sample mean) about potential values of point estimators of the parameter of interest under an assumed true value for the parameter of interest. These lack the quantitative measures of uncertainty about the parameter of interest itself. Even if the population mean was known exactly, the potential point estimators still have non-zero variance.

The inherent subjectivity of the Bayesian inference has been used as an argument against the Bayesian approach (Van Dongen, 2006; Senn, 2011; Blasco, 2017). However, scientists who utilize frequentist statistics also use varying levels of (hidden) prior knowledge when comparing and discussing their results against the results from previous studies (Blasco, 2017). Therefore, when we draw conclusions from our results, based on either Bayesian or frequentist statistics, we do not base on only our data but also on the previous results. However, in Bayesian inference, the prior information is an explicit part of the analysis, which is more transparent and also more objective than qualitative comparison.

Figure 3 shows an example of a Bayesian Belief Network (BBN). A BBN is a probabilistic graphical causal model consisting of stochastic variables (nodes) and arcs connecting those variables, indicating probabilistic dependencies between each other (Korb & Nicholson, 2004; Carriger et al., 2016). These are specified via a directed acyclic graph (DAG). Each variable is defined by an individual (mutually exclusive) state, representing the specified possible conditions for each variable. Conditional probability distributions (CPD) are the quantitative element of BBN, given for the ("child") nodes having incoming links from their "parent" variables. The strengths of the dependencies between nodes are described in CPDs in a probabilistic manner. There are a variety of methods to define CPDs such as observed or modelled data (Article [II], Fernandes et al., 2012; Uusitalo et al., 2012; Rahikainen et al., 2014; Moe et al., 2016), earlier published studies and literature (Borsuk et al., 2006; Barton et al., 2008) and stakeholder or expert knowledge (Article

[III], O'Hagan et al., 2006; Mäntyniemi et al., 2013; Shaw et al., 2016). BBN can also be used for predictive inference from causes to their likely consequences, diagnostic inference from consequences to their likely causes, and omnidirectional mixed inference (Korb & Nicholson, 2004; Carriger et al., 2016).

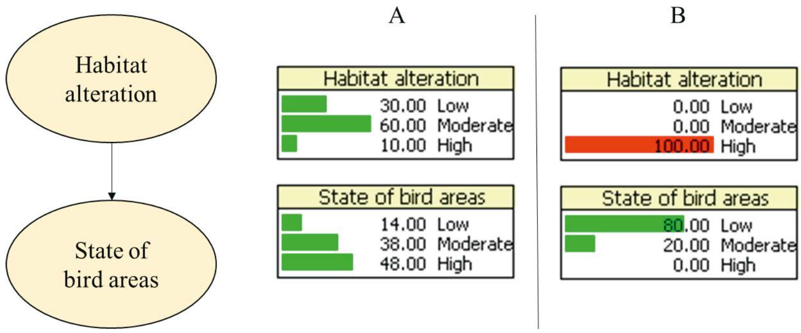

Figure 3. An example of a BBN with a hypothetical case. The state of bird areas is conditional to the habitat alteration variable; both are random variables having three alternative status classes (low, moderate, high). The case A shows the prior distributions that is the situation when the variables are not locked (i.e. observed). In case B, the red bar (P100%) indicate the locked state, e.g. the situation when we have observed high habitat alteration that further updates the beliefs about the state of bird areas. The values of each variable sum up to 100%, thus indicating the probabilities of each status class to occur.

Figure 4 shows an example of an influence diagram (ID) that is a generalization of a BBN, capable of solving decision-making problems under uncertainty (Nielsen and Jensen, 2009), therefore allowing complete decision analysis. There are three types of nodes in an ID: random nodes, decision nodes (that can be controlled e.g. policy options, management strategies), and utility nodes (that measure the utility or loss to be gained by selecting alternative decisions). The utility nodes express our relative preferences for all the possible output combinations of the target attributes. An ID calculates the expected utility (EU) given the state of knowledge and the decisions made in the network (Equation 2):

$$EU(d_i) = \sum_j U(h_j, d_i) P(h_j \mid X) \qquad (2)$$

, where $d_i$is the action i of the decision node, $h_j$is the state of the outcome variable, $U(h_j, d_i)$is the utility that is gained if the $h_j$comes true (when the action $d_i$has been taken), and X is the observed data.

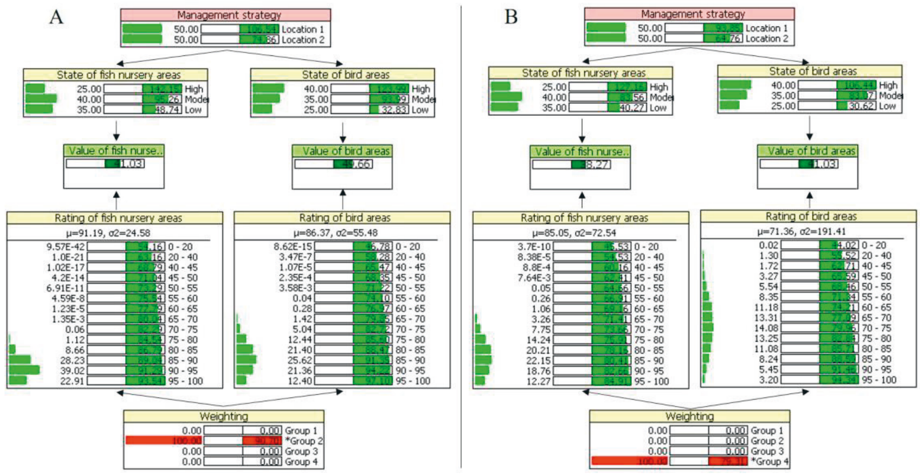

Figure 4. An example of an ID illustrated with a hypothetical case (modified from the Article [III]). The left side of the monitor windows shows the probabilities (summing up to 100%) of the alternative states of the (yellow-coloured) random variables. The right side of the monitor windows shows the alternative states of the random variables. State of the random variable *Weighting* represents the alternative stakeholder groups, defining whose opinion is taken into account in the calculation. In this model, the variable *Weighting* has to be selected (locked) to analyse the results. In case A and B, the red bars (P100%) show the locked states of the stakeholder groups 2 and 4 allowing to illustrate the computed posterior distributions reflecting the views of these selected (locked) stakeholder groups in the monitor windows for the *Rating of*...-random variables. Probability distributions of the *State of*...- random variables show the hypothetical states for the fish nursery and bird areas that are dependent on the state of the (pink-coloured) decision node (*Management strategy*). In this hypothetical case, the decision node includes two alternative locations (as Location 1 and 2) for the offshore wind farm. The resulting expected utilities for the fish nursery and bird areas are shown in the (green-coloured) utility (*Value of*...) nodes. The values shown within the bars of the random nodes express the total expected utility (summed over all the criteria) if the state in question is locked ("observed") next. The theoretical maximum total utility of for this example case is 2*100 = 200.

There are two main techniques to implement a Bayesian model; discrete and mixed state BBNs. In most cases, models can be implemented either way. When the models become complex with multiple continuous variables, calculating the posterior distributions becomes difficult and the analytical solution using Bayes' theorem is practically impossible. In this case it is possible to use either numerically approximated posteriors (Article [II] and

[III]) or discretized distributions (Article [III]). In many models, using discrete BBN models can be inadequate as discretizing variables results in information being lost, conditional probability tables can become too large, or the network with multiple variables linked to each other can become too substantial, as the variety of tools to create discrete BBN can be insufficient (Korb and Nicholson, 2004). Monte Carlo simulation is a common way to numerically approximate the posterior distribution by using randomly drawn values from the posterior distribution (Gilks et al., 1996). Therefore, the posteriors for the parameters can be estimated using Monte Carlo Markov Chain (MCMC) sampling with tools such as WinBUGS, OpenBUGS, and JAGS. Discrete BBN tools, such as Hugin software, can use continuous variables only when Gaussian (normal) distribution is used and a continuous node cannot be a parent of a discrete child node or used in IDs. The Bayesian models in this thesis have been analysed using Markov Chain Monte Carlo (MCMC) simulation methods with OpenBUGS (Spiegelhalter et al., 2007; Article [III]) and JAGS (Plummer 2003; Article [II]) software and discrete BBN with Hugin (Madsen et al., 2005; Article [III]) software.

3 RESULTS AND CONTRIBUTIONS

The following chapters approach these questions from the multidisciplinary and probabilistic standpoint, providing novel ideas and tools.

3.1 Selection of suitable indicators (Article [I])

When the qualitative verbal management objectives are set as "*Maintaining biodiversity*", "*Sustainable development*" or "*Good Environmental Status*", what do these mean precisely and how do we know when we have attained these objectives? The ambiguity of the definition can lead to difficulties in societal discourse and attaining common regional and international objectives (Borja et al., 2013). Using formal decision analysis requires that the objectives have measurable attributes that clearly reflect the attainment of the management objective. Thus, the attributes should be described in a quantitative and structured way, in order to define management objectives and assess the performance of environmental management (Rossberg et al., 2017). Selected attributes should capture dependencies of the system under study, *i.e.* to define how the direct and indirect pressures of the alternative management strategies are assumed to impact these attributes. However, to be able to measure the changes in attributes, quantitative indicators or metrics should be defined (Borja et al., 2013). Indicators are useful tools providing information about the current state and the changes of the selected attributes to the decision-makers as well as to society (Coll et al., 2016; Siddig et al., 2016). In the decision analysis, indicators can be used to better understand the causalities between the selected management activities and the environment (Coll et al., 2016; Olander et al., 2018).

Article [I] focuses on the management objective to maintain biodiversity, as it is one of the most important management objectives outlined in different international treaties such as the CBD (UNEP, 1992), in European Union (EU) legislations such as the Birds Directive (EEC, 2009), the Habitats Directive (ECC, 1992), as well as in the indicator-based management schemes such as Water Framework Directive (WFD; European Commission, 2000), BSAP

(HELCOM, 2007) and MSFD (European Commission, 2008). However, despite the wide-scale international efforts to implement policies and legislations that set objectives and guidance to protect the vulnerable species and habitats, global biodiversity is constantly declining in an accelerating rate (Fraixedas et al., 2019; Langhans et al., 2019). Biodiversity represents the diversity of life on Earth, thus it is a complex issue connecting different levels from genes to species (Féral, 2002), their functional forms and adaptations (Flynn et al., 2011), to the habitats and ecosystems together, not forgetting the variability within and between them (Whittaker, 1960, Magurran, 2004). There is considerably evidence that loss of biodiversity causes massive degradation of ecosystems (Pinto et al., 2014; Castello et al., 2016; Johnson et al., 2017), as well as the ecosystem functioning, stability, productivity, and services they provide (Cardinale et al., 2012; Isbell et al., 2017). Consequently, maintaining biodiversity is not just ecological, but also an economic and sociocultural matter.

Article [I] took a decision analytic viewpoint on quantitatively evaluating the environmental management against the loss or gain in biodiversity. Using the DPSIR framework, the likely impact of the alternative environmental management action on biodiversity is represented by the *State change* – element (Fig. 2) that could refer to the change in the ecological attributes. Furthermore, the *Impacts on society*- element includes the human perspective, thus determining the degree of the impact on the societal preferences, *i.e.* how the society values or weighs the loss or gain in the decision criteria defined by these attributes (Fig. 2). Thus, Article [I] analysed the economic, sociocultural and ecological indicator approaches for measuring the value of biodiversity in environmental management.

In monetary valuation, the impact of change in biodiversity by implementing alternative management actions are quantified by economic or human welfare values. The economic perspective can offer globally comparative values and provides the link between the environmental problem and political decision-making processes (TEEB, 2010a). Ecosystem services, *i.e.* the benefits people extract from ecosystems, are one way to quantify biodiversity in economic terms (Lamarque et al., 2011, Mace et al., 2012).

Ecosystem services can be divided into provisioning (e.g. production of food and water), regulating and maintenance (e.g. natural hazard regulation, water purification, pest control) and cultural services (e.g. spiritual, recreational, historical, scientific) (Haines-Young and Potschin, 2018). Therefore, the role of biodiversity in ecosystem services can be either a regulator of ecosystem processes, a final ecosystem service or a good (Mace et al., 2012).

However, the sociocultural values can alternatively provide information on how nature is appreciated without any link to the monetary value. Local people may have cultural or spiritual values for ecological components or regions (TEEB, 2010b) that provide different ethical and cultural values and mental well-being for the society (Christie et al., 2012; James et al., 2013). For instance, the knowledge and values from indigenous people can widen the scope and the objective setting of environmental management (Parviainen et al., 2019). For instance, Article [III] demonstrates how societal values can be incorporated in the decision analysis model to be used as a decision criteria to improve mutual understanding in environmental decision-making. However, the distinction between the economic or human welfare and societal wellbeing is not always straightforward. The social values and more importantly social wellbeing related to the cultural ecosystem services are understudied as the services are usually valued only in economic terms (Schmidt et al., 2016).

In sustainable environmental management, the ecological value forms the foundation when measuring whether the management objectives are met or not (Fig. 1). The ecological aspect can be measured by using classical biodiversity indices that describe the richness and distribution of species (e.g. the Shannon–Weiner diversity and the Berger–Parker indices [Hill, 1973], Pielou's evenness index [Pielou, 1969]). When we set target states for these indices, it defines the minimum level of biodiversity that society seeks to preserve. Thus, setting target states denotes the first social aspects of the decision analysis to determine whether the satisfactory level of biodiversity is achieved or not. To capture the complexity of the ecological system, Table 2 in Article [I] shows more holistic eco-social approaches that integrate the weights and target level setting by the expert or stakeholder together with estimates of the functional and structural status of the systems.

Article [I] suggests integrating these three perspectives of valuing biodiversity into a multi-objective EBM framework to consider the comprehensive ecological status as well as the economic and sociocultural importance of a healthy ecosystem. In the proposed holistic decision-making process, sociocultural values could indicate the ecological target attributes and ecosystem services that are most significant for society, whereas a price on loss or gain of biodiversity could provide globally more comparative and plausible values. Ecological indicators could be used as a basis of the decision analysis offering quantitative measures and threshold values that inform about the role of biodiversity in the health of ecosystems. However, to integrate these three perspectives into a single decision analytic framework can be challenging and requires a lot of data and complicated integrative models from both the ecological impacts and monetary values together with the costs of implementing the management measures.

3.2 Sufficiently good status of an indicator (Article [II])

Society selects different ecological, economic and sociocultural indicators outlining what an appropriately good status of the environment should look like and when the management objectives are attained (Article [I]). Next, after an appropriate set of indicators are selected, there is a need for further study on what these indicators actually measure and how much uncertainty is related to these measurements.

In the status evaluation schemes such as WFD (European Commission, 2000), BSAP (HELCOM, 2007) and MSFD (European Commission, 2008), ecological indicators are commonly utilized approaches to use information from the monitoring programs that assess trends and changes in system over time (Danovaro et al., 2016). The information is used in the indicator-based approaches to compare the prevailing status of a system to a reference condition or value assumed to reflect sustainable conditions, and thus denote the target state of the ecosystem. Thus, according to the MSFD, based on the target state, the boundary value differentiating the desirable (Good

Environmental Status "GES") from the undesirable ("Sub-GES") states of the system, is defined.

However, it is not straightforward to set the boundary value of an indicator to be used in decision-making due to imperfect knowledge about the actual status of a system. The sources of uncertainty when making inferences about the actual state of a system are manifold. Natural processes cause variation due to abiotic (e.g. temperature, precipitation) and biotic (e.g. predation, cohort-dynamics) factors, in contrast to human-induced variation due processes such as climate change, eutrophication and introduction of invasive species. Additionally, sampling procedures involve multiple sources of errors linked to the estimation of the actual state of a system, due to natural variation between the sampling sites, differences in sampling protocols and inadequate sampling effort (Borja et al., 2014; Carstensen & Lindegarth, 2016; Wach et al., 2019).

Uncertainty related to indicator values have been studied earlier (Balsby et al., 2013; Lehikoinen et al., 2014; Probst, 2017), however, in these studies the definition of the boundary value(s), have been considered as fixed, lacking the estimates of uncertainty. Article [II] claims that acknowledging the uncertainty related to the boundary value of an indicator is also significant, as it sets criterion that is used when evaluating the need for management and conservation decisions, as well as the level of sustainable use of the ecosystem services. For instance, if the uncertainty is not acknowledged and handled properly, the state of an indicator can be misclassified as desirable, when in reality it is not, leading to wrong management actions to be taken (Moe et al., 2015).

Thus, Article [II] presented a Bayesian approach to status evaluation that was applied to an ecological indicator currently used in the regional status assessment in the Baltic Sea, 'Abundance of coastal key fish species' (HELCOM, 2018). Bayesian statistics is proposed as it estimates the epistemic uncertainty about the unknown parameter, *i.e.* the *true state of the system*. The true state of the system is always a hidden variable that cannot be directly observed but represents the ultimate variable of interest. As a first step, this developed approach studied the variation of the population abundance index inferred from the scientific fisheries-independent data. This step aimed to filter out the observation variation and leave only the true population variation in the population abundance index. Thus, the real population relative abundance can be said to lie between the estimated credible intervals of the probability distribution (Fig. 5).

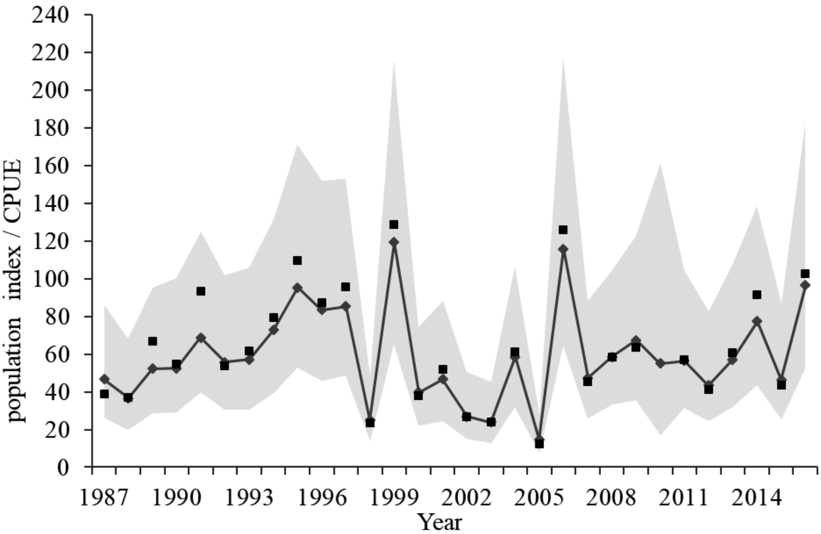

Figure 5. Medians of the posterior distributions for the population abundance indexes (dark grey line with the grey dots) with 95% posterior credible interval (shaded area) compared to the point estimates (catch per unit effort [CPUE] data) (black dots). The figure is modified from Article [II].

As the posterior distributions of population abundance indexes were approximated by Markov Chain Monte Carlo (MCMC) sampling, figure 6 illustrates the next step of the developed approach to use these posterior distributions of population abundance indexes in status evaluation rather than an estimator (the CPUE data in Fig. 5) that is a direct function of data. Such point estimators include both variation of the population and variation caused by the sampling procedure, which means that the estimators are more variable than the actual population. Here, each MCMC simulation is seen as a random sample from the posterior distributions of population indexes, and denotes a hypothesis about the relative variation of the populations. The suggested probabilistic status evaluation is done for each MCMC simulation at a time by calculating the GES boundary for both the 5th and 50th percentiles from *the* *resampled distribution of medians of the baseline period* and comparing it to the *median of the assessment period* (Fig. 6A). Then, after all the MCMC simulations, the probability distribution for the GES boundary, *i.e.* P(GES boundary) (Fig. 6B), and the overall probabilistic status evaluation indicating whether the GES is attained or not (Fig. 6C) are computed.

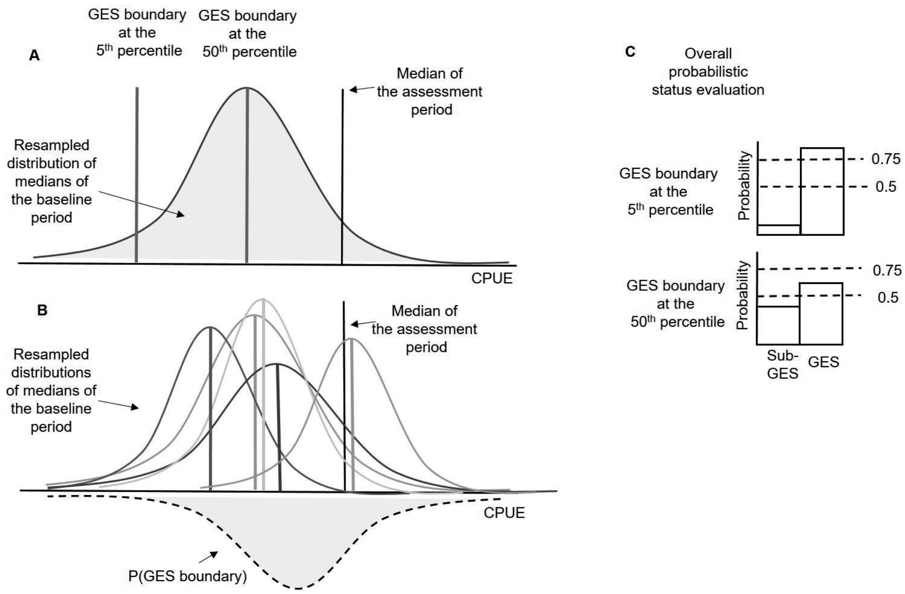

Figure 6. Schematic illustration of the proposed probabilistic status evaluation protocol. (A) Depicts the different GES boundaries at 5th and 50th percentiles estimated from the *resampled distribution of medians of the baseline period*. The selected GES boundary is then compared to the *median of the assessment period* to produce information on whether the GES is attained or not. (B) Shows how these steps are repeated for *X* MCMC simulations to produce the probability distribution *P(GES boundary)* for the GES boundary at 50th percentile. Then, (C) illustrates the resulting probability distribution P(GES) estimating the uncertainty related to the final classification result as well as how the selected safety marginal is used to set the required level of certainty to judge whether the management objective is attained or not. For instance, if the GES boundary at 50th percentile is selected with the safety marginal set to 0.75 (C), the probability of the status being GES is under the defined safety marginal, which denotes that the GES -judgement should not be made under the prevalent uncertainty. The figure is modified from Article [II].

The spatial and temporal uncertainty levels of the indicator-based status assessment (e.g. the WFD, BSAP and MSFD) vary across different spatial assessment units causing uneven uncertainty in the accuracy of the assessment units (Borja & Elliott 2013; Carstensen, 2014; Fleming-Lehtinen et al., 2015). The uneven distributions of monitoring locations across

European Seas (Patrício et al., 2016b) may lead to a lack of appropriate data for the assessments and difficulties in to the use of agreed indicators for instance in the MSFD. As Bayesian inference gives probabilistic uncertainty estimates for the parameters of interest based on the available data (McNeish, 2016), Article [II] proposes to use this type of approach in areas where the systematic monitoring and time-series data are relatively shorter or discontinuous.

To define the target level and set the corresponding boundary value for an ecological indicator can be difficult due to the uncertainty about the actual status of the system. The results of Article [II] shows how the Bayesian inference can be used to infer the level of knowledge we actually have, when it comes to the hidden GES boundary value. The developed probabilistic GES boundary allows holistic acknowledgement of the epistemic uncertainty arising from the variation related to the observation process and thus reduce the risk of misclassification. When the uncertainty behind the classification result is transparently presented to the decision-makers it may lead to more transparent and better-informed decision-making. In addition to this, the probability distribution of the GES boundary requires the decision-makers to state the acceptable level of risk for the potential misclassification, thus being transparent about their risk attitude (Fig. 6C). As the information concerning the amount and type of uncertainty may alter the risk attitude (Chow and Sarin, 2002), it can have an impact on the conservation or restoration decisions based on the indicator-based status assessments. Thus, the risk attitude plays significant part in the decision-making process, as it may affect the decision-maker's definition of the need for management actions (Burgman, 2005; Keith, 2009; Brunette et al., 2017).

Consequently, with the probabilistic classification result, the decision-makers have to make a statement regarding the acceptable safety marginal for the risk of misclassification of an indicator's status. The probabilistic safety marginals have been also used e.g. in the management of the Baltic salmon (*Salmo salar*) stocks (Kuikka et al., 2014; ICES, 2019). The safety marginal operates behind the final judgement of the decision-maker, setting the required level of certainty to judge whether the management objective is attained or not. For instance, when the safety marginal is set to 0.75, GES would be achieved with the minimum probability of 0.75 (Figure 6C).

Article [II] also highlighted the importance to recognize the ways in which the uncertainty in the environmental management process is communicated. However, the uncertainty in the status evaluation should not be taken as a sign for inaction or hesitation to proceed with management measures; instead, it should be seen as a call for more information (De Santo, 2010). Even though the remediation measures are costly, neglecting them due to uncertain results can cause even higher expenses (Nygård et al., 2016).

3.3 The role of values in multi-criteria decision-making (Article [III])

Whether the respondent would be a member of the public, industry, or government party, protecting, enhancing and sustainably managing environmental resources is seen as an extremely important process. However, environmental management problems are usually *wicked* and thus lack a unanimous definition (Rittel and Webber 1973). Therefore, while management objectives to protect and enhance the environment are ambitious, the meaning for different stakeholders is not the same (Voinov, 2017). Participatory modelling involving multiple stakeholders in the process of formal decision analysis can be a useful approach when dealing with *wicked problems* (Voinov et al., 2016; Voinov, 2017). Participatory modelling can increase transparency and improve the mutual understanding between participants (Voinov and Bousquet, 2010; Voinov et al., 2016). When decision-making aims for a collectively fair outcome, any stakeholder who has an interest or is affected by the management decisions should be heard (Dietz, 2003; Gopnik et al., 2012). When multiple stakeholders are involved in decision-making, interdependencies and power relationships among the participants become significant, which can have an impact on the overall process (Kørnøv and Thissen, 2000). Even though all the views should be considered, it may not always be possible or even necessary to weigh them equally (Dietz, 2003). Society's commitment to management decisions have found to affect the level on which the new regulations and rules are followed, and thus affect the effectiveness of the management (Jones et al., 2011; Haapasaari et al., 2012).

In a specific decision-making problem, the attributes that are affected by the decisions and thus should be protected are needed to be specified. Therefore, to be able to rank the alternative management actions or policies between each other, the *weigh* or *value* for each of the attributes should be provided. Even when there are two contrasting ecological attributes (e.g. fish nursery area and important bird area), the information of their ecological characteristics such as vulnerability, conservation status or abundance is needed to be able to select the action that provides the highest utility. In turn, the decision analysis becomes more complicated when the economic or sociocultural aspects are included in the analysis as required in the EBM framework.

The role of valuation has a significant role in participatory decision-making, as the perceived utility or harm is always perspective-dependent and thus the defined decision criteria reflect the views who have set them up (Schiller et al., 2001). Stakeholder involvement often creates several, contradictory decision criteria to evaluate whether the management objective is attained or not. Thus, when several decision criteria are set, there is a need to determine how and from which perspective the decision criteria should be weighted in relation to each other. The Multi-Criteria Decision Analysis (MCDA) is an approach used to frame decision-making problems with multiple decision criteria to measure the level of attainment of the management objectives (Huang et al., 2011). However, the inevitable trade-offs in environmental MCDA easily lead to conflicts, as the society's voice is not uniform because divergent stakeholder groups have their opposing views and interests towards the services and benefits ecosystems provide (Langemeyer et al., 2016).

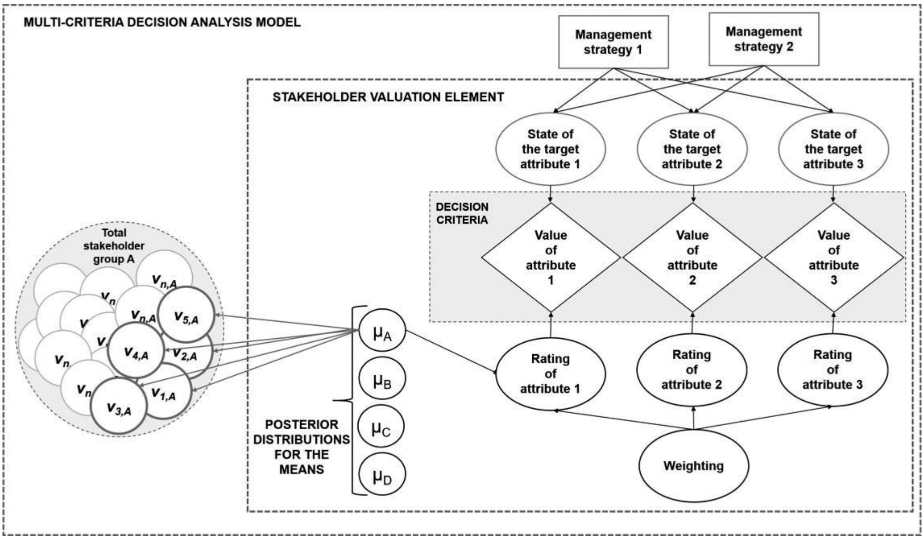

Figure 7. Illustration of the sequential BBN framework. The figure is modified from Article [III].

The participants' views within stakeholder groups also vary considerably and thus should be transparently acknowledged. Article [III] demonstrated how the information of participants' opposing attitudes and values can be utilized, in a way that the collective opinion of each stakeholder group could be used as decision criteria to evaluate and rank the alternative management actions between each other. Article [III] suggested the sequential BBN modelling framework integrating both the continuous and discrete state BBN models (Fig. 7). Here, the probabilistic approach is introduced to quantify the uncertainty about the stakeholder groups' consensus concerning the rating of the key target attributes. The approach allows to generalise the views for the entire stakeholder group instead of only the participants in a collected sample. Thus, the developed continuous state BBN model provides the results as distribution-form decision criteria allowing to state that the real value lies within a certain credible interval (posterior distributions for the means in the Fig. 7).

The second part of the sequential BBN model was to integrate the distribution-form decision criteria (*posterior distributions for the means* in the Fig. 7) in a discrete state BBN model to visualise transparently the level of disagreement or agreement regarding the decision criteria (*Stakeholder valuation element* in the Fig. 7). For instance, researchers and non-governmental organizations may have contradictory views on how the decision criteria should be valued or weighed, related to other stakeholder groups whose views can be influenced by different economic, ecological or sociocultural perspectives. The graphical tool developed utilizing the Hugin software, provides a transparent and interactive presentation to support discussion between stakeholder groups and learn more about each other's thinking.

Furthermore, Article [III] demonstrated how the *Stakeholder valuation element* could function as a part of a MCDA model. Here, the *Stakeholder valuation element* was extended to an ID by adding two decision nodes. As part of a MCDA, the valuation element can be used as decision criteria, in a probabilistic evaluation of the alternative strategies, guiding managers to select socially more optimal and acceptable solutions by comparing the views from different stakeholders. As a hypothetical example, a manager could have a situation where the decision-making includes the selection between two alternative routes (as *Route 1* and *2)* for the maritime traffic (*Management strategy 1* in Fig. 7). Both of the routes could create divergent pressures on the environment, which then could cause changes in the environment status (*State of target attribute 1, 2* and *3* in Fig. 7). Thus, the manager could select the route that causes less harm for the environment and society, *i.e.* providing the highest total expected utility. Alternatively, the manager might need to find the most optimal solution between the two (or more) parallel management strategies, for instance, *Management strategy 1* together with *Management strategy 2*, which could include two alternative locations (as *Location 1* and *2*) for the offshore wind farm (Fig. 7). The selection between the alternative strategies could create a decision-making dilemma as *Location 1* could be in the same vicinity of *Route 1* when the decision could be either to centralize the actions and consequently cause higher pressure in one location but alternatively keep other areas untouched. Another possibility could be to distribute the activities where the pressure per area is lower but allocated to a larger area.

Using the *stakeholder valuation element*, managers could analyse whether the centralized allocation of pressure is a more socially optimal decision than distributing the actions (Article [III]). As *wicked* environmental management problems are challenging to solve, the developed approach offers a transparent way to find a solution that represents the optimal compromise in the presence of potentially conflicting objectives.

4 DISCUSSION

This thesis elaborates on the important question how – in the presence of uncertainties arising from numerous sources, combined with varying ways of interpretation and prioritization by people - society can define whether its environmental quality objectives are met and consequently, whether actions for attaining them in the future are needed. Through one review article and two research articles, the thesis explores this question by drawing special attention to multidisciplinary approaches, acknowledging the interplay of the environmental data and human values behind the environmental decision-making processes. To tackle the uncertainties, special effort is put on applying Bayesian modelling methods and normative decision theory to approach the presented question and to develop tools that could advance informed and collectively good environmental decision-making.

Rationality in decision-making can be viewed as the rationality of the procedure (*i.e.* defining the objectives, identifying and evaluating alternative actions or policies to implementation and monitoring) or as the rationality of the process outcome (*i.e.* selection of the alternative that maximizes the utility) (Kørnøv and Thissen, 2000). Rationality in the procedure does not always result in rational and satisfying outcomes due to imperfect knowledge, multiple preferences and unrecognized values, as well as potentially irrational human behaviour (Kørnøv and Thissen, 2000). These can even cause the rejection of the illogical or unclear outcome (Calabretta et al., 2017). This thesis developed methods to support the rational outcome.

Ecological indices, based on monitoring data and statistics, can be used as target attributes in environmental quality assessments. However, the indices as such may be inadequate measures to support decision-making, as in the presence of multiple target attributes there is a need to take a stand on their mutual weighting (Ruiz-Frau et al., 2011; Kobryn et al., 2018), which means value statements have to be brought in. For example, an endangered species may for ecological reasons be valued higher than a least-concern species; that is, higher diversity of species leads to more resilient ecosystems, thus the loss of species is something to be avoided (Ihaksi et al., 2011). However, endangered species can also be valued from an ethical viewpoint, that is, humans have no right to destroy species. Some species may matter to people in monetary terms. For instance, fishermen's livelihood is tightly linked to healthy fish populations. At the same time, the same fish may have high sociocultural importance in terms of e.g. the cultural heritage of fishing and the local communities built on it (Reed et al., 2013; Acott et al., 2014; Ignatius et al., 2019). When conducting the literature review and analysis for Article [I], I realised the underlying reasoning behind the perceived value of an attribute is a mixture of preferences and separating these can be challenging. There has clearly been a need for such sort of an analysis, as Article [I] has been read extensively and been well cited based on data retrieved from several databases (e.g. Mendeley, Scopus, Web of Science).

Uncertainty is generally defined as the lack of precise knowledge about the system under study (Refsgaard et al., 2007; Ascough et al., 2008). Thus, with any approach, epistemic uncertainty about the actual state of the system is unavoidable. However, new information about the system does not always reduce the uncertainty as additional knowledge may reveal uncertainties that were not known or understood previously (Walker et al., 2003). On the other hand, by adding new knowledge into the system, it is possible to acknowledge the limitations of our understanding (van der Sluis, 1997). The advantage of using Bayesian statistical modelling tools is that these models estimate the inherent epistemic uncertainty, and correspondingly, the level of prevailing knowledge about the system. As Bayesian model allows us to include our prior knowledge about the system and causalities between the model parameters, our past understanding can actually help to achieve more logical and clear model results together with new data.

Even though the quantitative target levels of the indicators are essential in environmental decision-making, in the end, how they are interpreted in decision-making is crucial. When modelling tools are used to assist decision-making, the emphasis should be to ensure that information provided by the model result is understood unequivocally by both the statistical modeller and the decision-maker (Cartwright et al., 2016). In practice, this can be a challenging task, as the scope and extent of decision-making can vary widely at various scales from local to global governance (Bennett and Satterfield, 2018). For instance, all large-scale policy processes (e.g. the adoption and implementation of the MSFD) involve large numbers of independent parties or actors to facilitate negotiations and debates to achieve an optimal solution. It is clear that when we are dealing with large-scale issues the preferences and selected risk attitudes can vary highly between the actors. Therefore, such probabilistic approaches might ultimately complicate the already complex decision-making process. I think that the probabilistic approach shows significant potential to solve real environmental policy and management problems, but care should be taken on how and from whose viewpoint the risk attitude for the target level are set and how well the scientific knowledge is understood by the decision-makers.

Vague definition of environmental management objectives complexify societal discourse (Cummings et al 2018). As the effects of the management measures are perceived differently between actors, an important part of environmental decision-making is to communicate the diverse values and preferences that people hold and assign to the environment (Walz et al., 2019). Participatory processes can speed up the integration of scientific results into actions by integrating societal values as an inherent part of the modelling (Voinov et al., 2014). Thus, by improving the awareness of each other's preferences and reasoning behind them can advance collectively fair decision-making (Dietz, 2003; Gopnik et al., 2012). The collaborative decision-making framework suggested in Article [III] could improve the understanding of both decision makers and stakeholders on the unavoidable compromises and uncertainties related to the decisions that are required. In addition to this, participatory processes can also be seen as a way to share knowledge and understanding.

Trade-offs between the alternative management measures cannot be avoided when making management decisions to solve *wicked* environmental problems. Decision-makers are often required to make a decision to either favor environmental protection over the regional employment and economic growth or vice versa (Naughton-Treves et al., 2005; Minteer and Miller, 2011). However, these objectives do not always diminish each other. When decision makers have holistic understanding of the complex and multidisciplinary decision-making problem including the ecological, economic and sociocultural values, it is possible to make decisions that are more acceptable and just. I hope that these ideas and tools developed in this thesis will be useful when trying to find solutions for the complex environmental management problems, as well as promote more multidisciplinary viewpoint decision-making.

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